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Comparing three spatial prediction results in mapping soil textural class names Using USDA soil textural triangle in the case of Dugdadistrict, Ethiopia.

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Abstract-*This study aimed to compare spatial prediction results to map soil textural class names using laboratory results of soil textural properties (sand, silt, and clay) based on USDA soil textural triangle classes' boundary definitions. The study has been done in Dugda district, Oromiya Region, Ethiopia. The study area has been divided into 126 mapping units based on soil-forming factors and soil samples were collected at depths of 0 to 20 cm from each mapping unit. The soil samples were analyzed at the laboratory for textual proportions. These results were used in spatial prediction methods inverse distance weighted, ordinary kriging, and random forest to get continuous raster maps for sand, silt, and clay. The raster maps were used as input layers to develop the twelve soil textural class names of USDA definitions in the raster calculator of spatial analysis. The results have revealed using the inverse distance weighted method has seven textural class names (Clay, Clay loam, Sand clay loam, Silt loam, Loam, Sandy Loam, and Loamy sand). When using ordinary kriging interpolation, four textural class names (Clay loam, Loam, Sand clay loam, and sandy loam) have been existing. Similarly, using random forest algorithm prediction has four textural class names (Clay loam, Loam, Sand clay loam, and sandy loam). Even though at least four textural class names exist in all the prediction methods, the dominating textural class name is loam which accounts for 87.11%, 96.99%, and 95.23% in inverse distance weighted, ordinary kriging, and random forest respectively.*
Keywords*- IDW, OK, RF, Soil texture, spatial analysis, and USDA.*

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I. Introduction

Soil texture is a vital variable that exposes several soil properties such as soil permeability,water holding capacity, nutrient storage and availability, and *soil* erodibility [1]. likewise, the soil texture has an impact on soil microbial activities;[2] informed that soil microbes have a more substantial impact on tropical sandy soil than on clayey soil in acting as a nutrient pool and decomposers. consistent with [3] contents of soil clay and silt were correlated to earthworm abundance in addition to the abundance of hymenoptera was related to silt content.

Mapping the soil textural class name using discrete soil point dataset as a continuous surface map from sand, silt, and clay proportion analyzed at the laboratory is very illative for related soil properties. The examination of spatial variability of soil texture at a detailed scale is vital for several activities like agricultural production and environmental management [4]. However, the determination of soil texture class started with the feel method, which depends on interpretation by hand management and is associated with a high error in estimation [5]currently, it is at the stage of a more reliable method of determining soil texture analysis in the laboratory and estimating from bands of remote sensing sensors [6].

Generating map of the area in soil textural names based on the revisedUnited States Department ofAgriculture (USDA) [7] soil textural class boundary definitions of twelve classifications such as sand, loamy sand, sandy loam, loam, silt loam, silt, sandy clay loam, clay loam, silty clay loam, sandy clay, silty clay, and clay in continues map coverage for an area of land need somewhat composite implementation of spatial analysis and models. The soil mapping unit approach considers dominant components and some minor components that influence easily perceptible natural properties of soil and fix the textural class name based on the mapping unit boundary. Digital Soil Map (DSM) used geostatistical interpolation techniques for predicting continuous properties for non-sampled locations [8]. However, the prediction methods are advancing to machine learning approaches that use many algorithms the most popular is predicting by random forest method.

In the case of the Dugda district, farmers and other stakeholders frequently ask the basic soil information about their farmland for irrigation and fertilizer management of their agricultural practices. Hence, it was very tedious to do once for all areas of the whole district, which sums up to 92,000hectares as response Batu Soil Research Center had planned to map soil fertility status and collected about 126 soil samples from unique mapping units. For all 126 sample points of soil data, they analyzed at a laboratory for soil textural proportions of sand, silt, and clay in percent, but not mapped as revised USDA soil textural triangle class boundary definitions. Hence creating a map as USDA definitions need integrating geostatistical interpolation, Machin learning algorithms, and a raster calculator approach to spatial analysis.

The predicting values for non-sampled locations change the discrete point data to continuous information of the total area. Samples points were from many composite points and central to the mapping unit. The adjacent mapping units were separated based on factors; slope, aspect, parent material, land use, drainage density, rainfall, and temperature of the study site. Since outputs maps are expected to infer other soil properties to use the information for any land management practices, predicted soil textural values should be integrated more accurately and effectively to determine the soil textural names. Hence the study is aimed to compare alternative prediction methods' results and to produce the output soil textural class names map. Here are models for soil textural class name map preparation and soil texture class percentage for the Dugda district based on USDA soil textural triangle class boundary definitions. The study also helps in using the approach developed here to use for other study areas by only changing the input datasets of an area.

II. Materials And Methods

2.1 Description of Study Area

2.1.1 Location

The study was conducted in Dugda District of East Showa zone, Oromiya Region, which is 145km to south west of the capital city Addis Ababa, Ethiopia. The extent of the study area ranges from $38.5241^0$to 38.9618^0 the east and $8.0317^0$to $8.3929^0$to the North. The location map of the study area is as in Figure1.

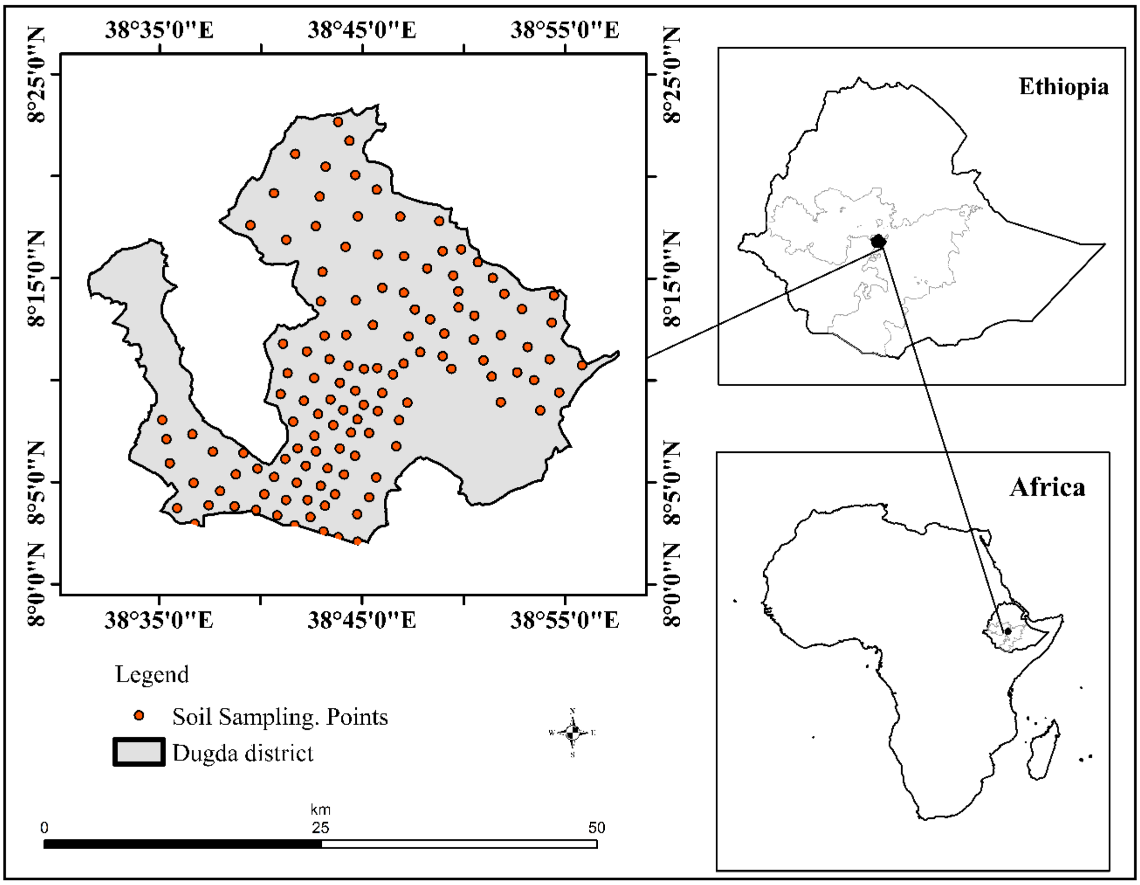

FIGURE 1: Location Map of Study Area

2.1.2 Elevation

The study area has minimum elevation of 1665 meters and maximum elevation 2367meters with average of 1755meters above sea level which can be categorized as mid land.

2.1.3 *Slope*

The slope ranges from0 to maximum slope 164.76percent. As a result, thestudy area is mainly dominated by flat and gentle topography, thus average slope of the study area is 4.11percent.

2.1.4 *Climate*

When the climate is considered, the two main elements are rainfall and the temperature of an area. Both have their unique measurement and description method. In the case of Dugda, the climate is warm and temperate. The summers here have a good deal of rainfall, while the winters have very little. This location is classified as BSh by Köppen and Geiger[9]. The average annual temperature is about 19.3 °C in Batu. In a year, the average rainfall is about 837 mm.

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2.1.5 *Temperature and Precipitation*

April is the warmest month with an average temperature of 20.4 °C while December is the coldest month with average temperature of about 17.6°C. The precipitation varies 141 mm between the driest month and the wettest month. Throughout the year, temperatures vary by 2.8 °C [9].

2.2 *Methods*

2.2.1 *Soil sample collection*

2.2.1.1 *Mapping unit delineation*

Based on the Parent materials, Topography, drainage density and land use/cover the district divided into 126 mapping units by employing overlay analysis and digitization.

2.2.1.2 *Central point generation*

For each mapping unit, a central point/centroid and their coordinates points were determined by ArcGIS software. The coordinate points were used by uploading to hand-held GPS during the field soil samples collection surrounding center points of mapping units.

2.2.1.3 *Composite soil sample collection*

From each mapping unit, a single representative soil sample, which is composite made up of mixing 20 to 30 sub-composite random soil samples surrounding the center point within the mapping unit and taken to laboratory analysis. Totally 126 soil samples were collected to represent the whole study area.

2.2.1.4 *Laboratory soil sample analysis*

For each sample soil sample sand, silt, and clay percentage was determined by Hydrometer method at Batu SoilResearch Centre Laboratory[10].

2.3 *Data analysis*

Soil Sample analysis (Sand, Silt & Clay) percentage results descriptive statistics were summarized by attribute table statistics in ArcGISsoftware. The spatial statistics of the predicted textual values were also generated by raster processing in data management tool of ArcGIS software.

2.3.1 Geostatistical interpolation and random forest

The laboratory results of soil textural separate (Sand, Silt &Clay) percentage were used to predict continuous surface values for unsampled locations at grid cell of 30m by using RStudio platform. The resultsof inverse distance weighted, ordinary kriging, and random forest predictionmethods were generated as output map layers. The outputs of the three prediction methods were as indicated in Figure 2.

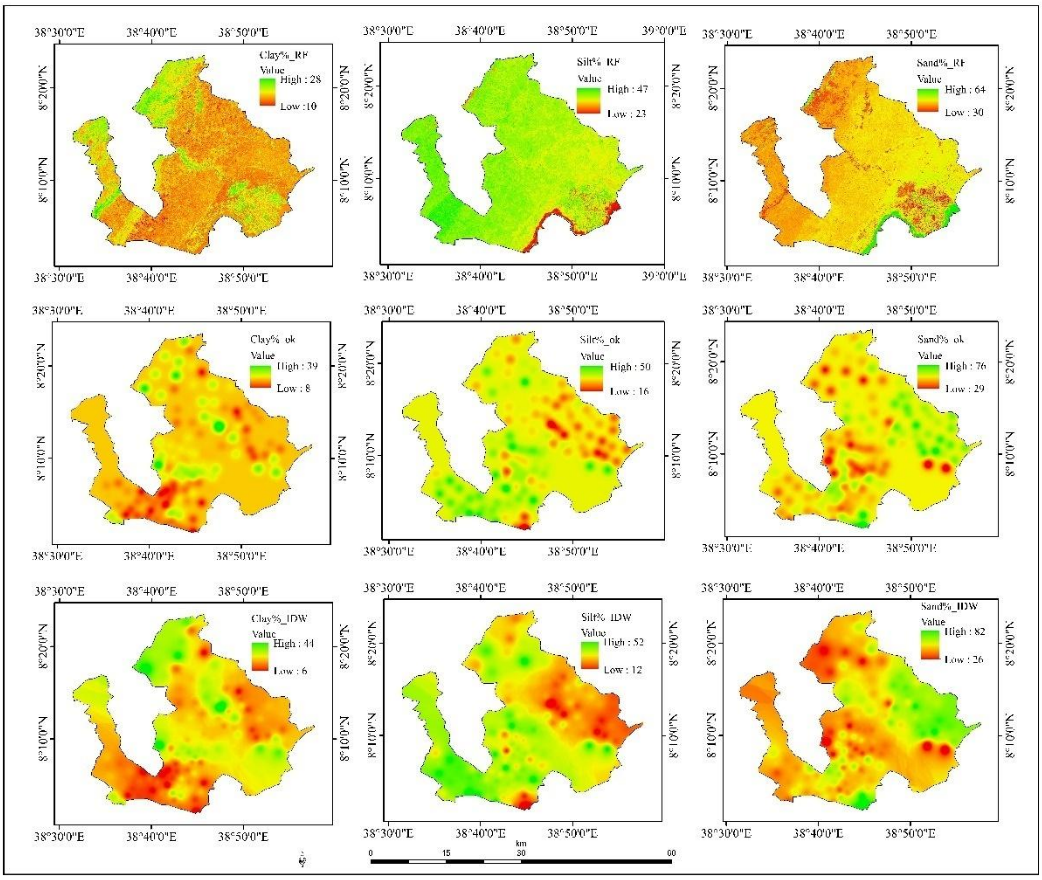

Figure 2: Soil Textural classesraster map

2.4 Modeling and mapping the soil Textural Class Names

Soil textures are classified using the fractions of each soil separate (Sand, Silt, and Clay) present in a soil. In this study, based on USDA soil textural triangle boundary definitions, from predicted values of (Sand%, Silt%, and Clay%) which is continuous raster layers, soil textural classes' names were developed by creating models in Model builder in ArcGIS software to combine the soil separates.The triangle has 12 different soil textural classes' names associated with various proportions of a soil (sand, silt, and clay). The dominant particle within each class provides the soil unit its characteristic textural class. The twelve classifications are (Sand, Loamy sand, Sandy loam, Loam, Silt loam, Silt, Sandy clay loam, Clay loam, Silt clay loam, Sandy clay, Silty clay, and Clay). In order to create maps of each class, the USDA definitions were applied in Raster Calculator of Map Algebra by Spatial Analyst tool of ArcGIS software Table1.

Table1: Revised Textural Class Definitions of USDA

No	Textural Class Name	Texture Class Definitions
1	Sand	A) Sand > 85% and Silt + (1.5 * Clay) < 15%
2	Loamy sand	A) Sand > 70% and Sand < 91% and Silt + 1.5 * Clay >= 15% and silt + 2 * Clay < 30%
3	Sandy loam	A) (Clay >= 7% and Clay < 20% and Sand > 52% and Silt + 2 * Clay >= 30%) or B) (Clay < 7% and Silt < 50% and Silt + 2 * Clay >= 30%)
4	Loam	A) Clay >= 7% and Clay < 27% and Silt >= 28% and Silt < 50% and Sand <= 52%
5	Silt loam	A) (Silt >= 50% and Clay >= 12% and Clay < 27%) or B) (Silt >= 50% and Silt < 80% and Clay < 12%)
6	Silt	A) Silt >= 80% and Clay < 12%
7	Sandclay loam	A) Clay >= 20% and Clay < 35% and Silt < 28% and Sand > 45%
8	Clay loam	A) Clay >= 27% and Clay < 40% and Sand > 20% and Sand <= 45%
9	Silt clay loam	A) Clay >= 27% and Clay < 40% and Sand <= 20%
10	Sandy clay	A) Clay >= 35% and Sand > 45%
11	Silt clay	A) Clay >= 40% and Silt >= 40%
12	Clay	A) Clay >= 40% and Sand <= 45% and Silt < 40%

Sources: https://www.nrcs.usda.gov

After the evaluation in raster calculation, raster outputs as (1: textural class name exists)/ (0:no textural class name exists) were produced based on USDA textural triangle boundary definitions. For each prediction method, textural class names' results are indicated inTable2.

Table 2:Textural class name results from each prediction methods

No	Textural Class Name	Inverse Distance weighted	Random Forest	Ordinary Kriging
1	Sand	0	0	0
2	Loamy sand	1	0	0
3	Sandy loam	1	1	1
4	loam	1	1	1
5	Silt loam	1	0	0
6	Silt	0	0	0
7	Sand clay loam	1	1	1
8	Clay loam	1	1	1
9	Silt clay loam	0	0	0
10	Sandy clay	0	0	0
11	Silt clay	0	0	0
12	Clay	1	0	0

Sources: Generated by using raster calculation

2.5 Merging textural class names Results

For each prediction method (Inverse Distance Weighted, Ordinary Kriging, & Random Forest), their existing (1: textural class name exists) table2 were merged to generate a single map for the Dugda district boundary. In case of inverse Distance weighted (Clay+ Clay loam+ Sand clay loam +Silt loam + Loam + Sandy loam + Loamy sand), Ordinary Kriging (Clay loam +Sand clay loam + Loam + Sandy loam), and Random Forest (Clay loam +Sand clay loam + Loam + Sandy loam) were merged in ArcGIS software.

2.6 Flow diagram to conduct the study

The overall flow diagram, which was used to accomplish the whole activities and models employed, geostatistical interpolations, random forest prediction, and evaluating input layers (prediction outputs) using revised USDA soil textural triangle class names' boundary definitions are indicated in Figure3.

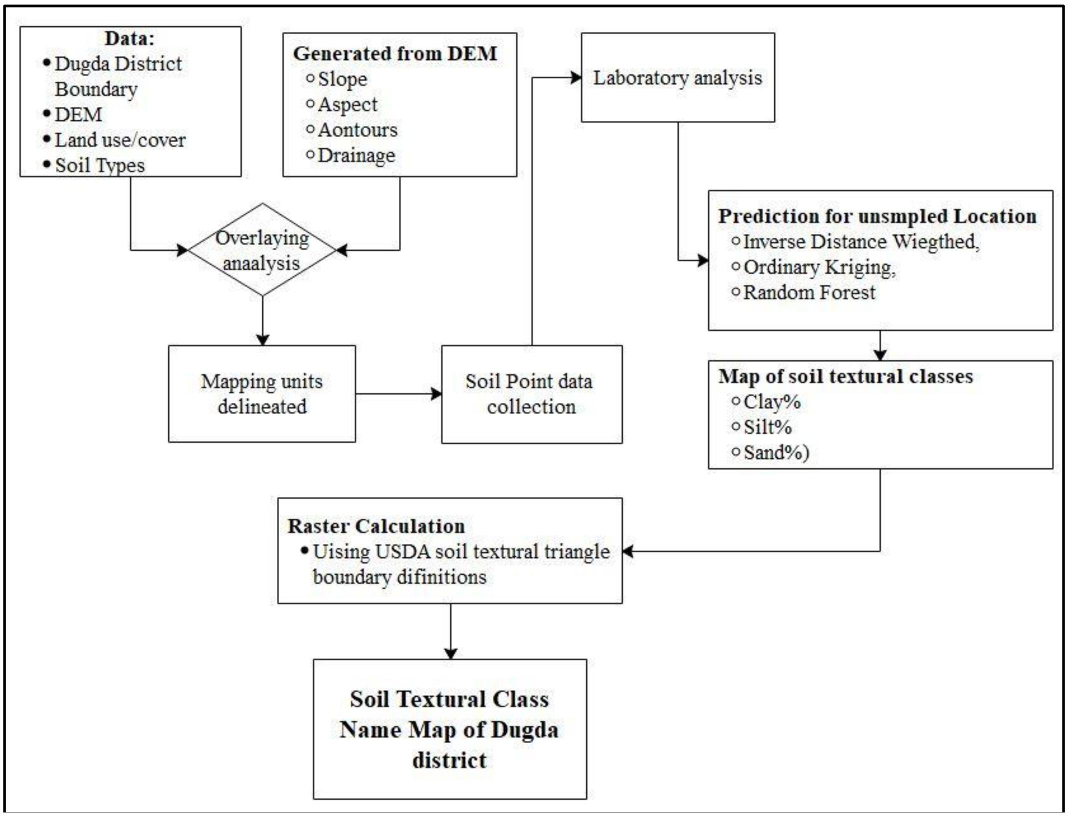

Figure 3: Flow Diagram for Soil Textural Classes Name Mapping

III. RESULTS AND DISCUSSION

3.1 Soil analysis results

The laboratory result values of soil sample points dataseti.e.,soiltextural proportions are summarized in Table 3. Sand% ranges from 26 to 82% with a mean of 45%. Silt% ranges from 6 to 52% with a mean of 38%, and Clay ranges from 6 to 44% with an average of 16 %.

Table 3: Textural Class Percentage Summary Statistics

Parameter	Sand%	Silt%	Clay%
Minimum	26	6	6
Maximum	82	52	44
Mean	45	38	16
Standard Deviation	8.33	6.45	5.85
Number of samples	126	126	126

3.2 Soil textural class prediction Results

The prediction results i.e., continuousrasterlayers (Sand, Silt and Clay) proportion are as indicated in Figure2.In inverse distance weighted interpolation sand% ranges from 26to82% with mean value of45%,Silt ranges between 12 to 52% with average of 38% and Clay ranges from 6 to44% having average of 17%. In the Ordinary kriging interpolation sand% ranges from 29 to 76% with mean value of45%,Silt ranges between16to 50% with average of 38% and Clay ranges from8 to39%having average of17%. In case the of random forces prediction sand% ranges from 30 to 64% with mean value of 45%, Silt ranges between 23 to 47% with average of 38% and Clay ranges from 10 to 29% having average of 17%. FromTable4 theaverage values have similar results in the cases of all prediction methods, while minimum and maximum values varying.

Table 4:Textural Class Summary Statistics of predicted continues raster layers

	Inverse Distance Weighted			Ordinary kriging			Random forest		
Statistics	Sand	Silt	Clay	Sand	Silt	Clay	Sand	Silt	Clay
Maximum	82	52	44	76	50	39	64	47	29
Minimum	26	12	6	29	16	8	30	23	10
Mean	45	38	17	45	38	17	45	38	17
Standard deviation	5.27	3.98	3.47	3.15	2.51	2.30	4.68	2.98	2.77

3.3 Map of soil textural class

After running the model developed for the study area, the soil textural class name maps were generated for the study area as fulfilling the conditions employed in the raster calculator from textural class boundary definitions for each class name. As result, while the inverse distance weighted method was used about seven textural class names (Clay, Clay loam, Sand clay loam, Silt loam, Loam, Sandy Loam, and Loamy sand) were found in the study area. Next when ordinary kriging interpolation was employed about four textural class names (Clay loam, Loam, Sand clay loam, and Sandy loam) were existing in the study area. Finally, whereas using random forest algorithm prediction about four textural class names (Clay loam, Loam, Sand clay loam, and Sandy loam) were found in the study area which is similar to using Ordinary Kriging interpolation, but the similarity stays true only for textural class names only, it is not true for the spatial distribution and area coverage Table5.

Even though at least four textural class names exist in all the prediction methods, the dominating textural class name is loam which accounts for 87.11%, 96.99%, and 95.23% in inverse distance weighted, ordinary kriging, and random forest respectively table5. Among 12 USDA soil textural class names, many of them are not existing in the study area at the scale used.

Table5: Area Coverage of Soil Textural Classes Names bythe three Prediction Methods

Prediction Method		Inverse Distance weighted			Ordinary Kriging			Random Forest		
no	Textural Name	Area(ha)	Area (%)	Rank	Area(ha)	Area (%)	Rank	Area(ha)	Area (%)	Rank
1	Clay loam	1192.39	1.30	3	394.44	0.429	3	3290.35	3.576	2
2	Loam	80141.94	87.11	1	89224.33	96.987	1	87630.17	95.234	1
3	Sand clay loam	106.23	0.12	4	2.58	0.003	4	1074.52	1.168	3
4	Sandy loam	10443.75	11.35	2	2375.22	2.582	2	20.54	0.022	4
5	Loamy sand	50.15	0.05	5						
6	Silt loam	24.17	0.03	7						
7	Clay	39.93	0.04	6						

3.4 Ranking the area coverage of the textural class names

The USDA soil textural class names that exist in the study area have different area coverage and orders for the three prediction methods. The IDW has similar order with OK (1:Loam, 2:Sandy loam, 3:Clay loam, & 4:Sandy clay loam), unlike RF has different order(1:Loam, 2:Clay loam, 3:Sandy clay loam, & 4:Sandy loam)Table5.

The spatial location similarity of soil textural class name for the three prediction methods is illustrated in the map Figure4. The Clay loam class name i.e.the second dominant class in the random forest method is highly populated near the southeastern part of Dugda where the area is adjacent to lake Dambal shore characterized by sedimentation.

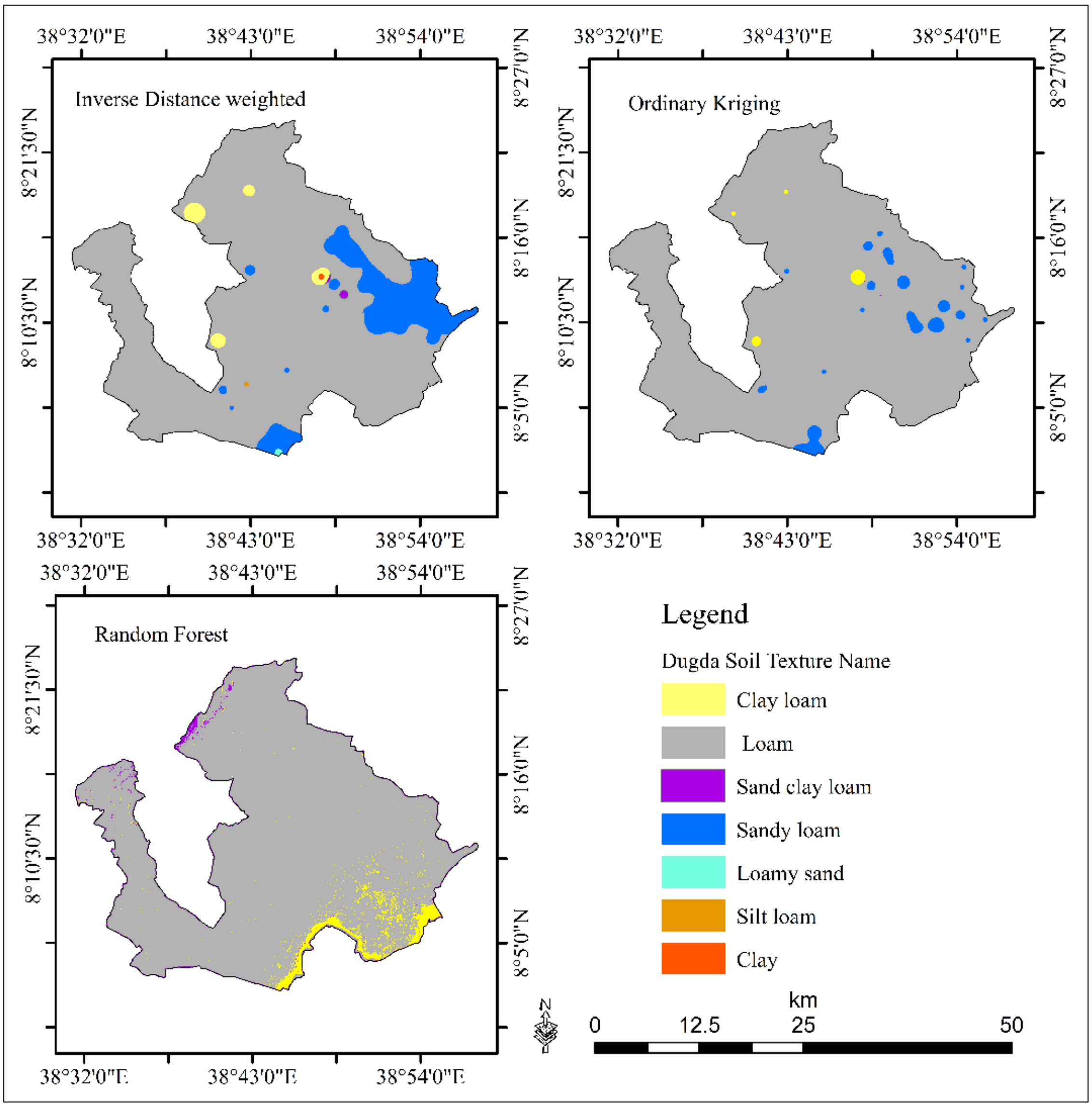

Figure 4: Map of soil textural classes'Name

IV. CONCLUSION

The study has done in Dugda district, Oromia Region, Ethiopia. It aimed to compare the results of three spatial soil properties prediction methods (IDW, OK, and RF) in soil textural class name mapping. It has used integration of spatial analysis to map soil textural class names from the laboratory analysis results of soil textural proportions based on USDA soil textural triangle classes' boundary definitions. The study area has been divided into 126 mapping units from which surface soil samples were collected and analyzed at the laboratory for relative textual proportions by hydrometer method. The laboratory results have been used in RStudio to predict continuous raster maps for sand, silt, and clay percentages by three prediction methods. The predicted raster maps were used as input layers to evaluate the twelve soil textural class names of USDA definitions in the raster calculator of the spatial analysis tool. The results have revealed using the inverse distance weighted method has about seven textural class names (Clay, Clay loam, Sand clay loam, Silt loam, Loam, Sandy Loam, and Loamy sand). When using ordinary kriging interpolation, four textural class names (Clay loam, Loam, Sand clay loam, and sandy loam) have been existing. Similarly, using random forest algorithm prediction has four textural class names (Clay loam, Loam, Sand clay loam, and sandy loam). Generally, loam has been the dominant class name of the study area in the cases of the three prediction methods.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper

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